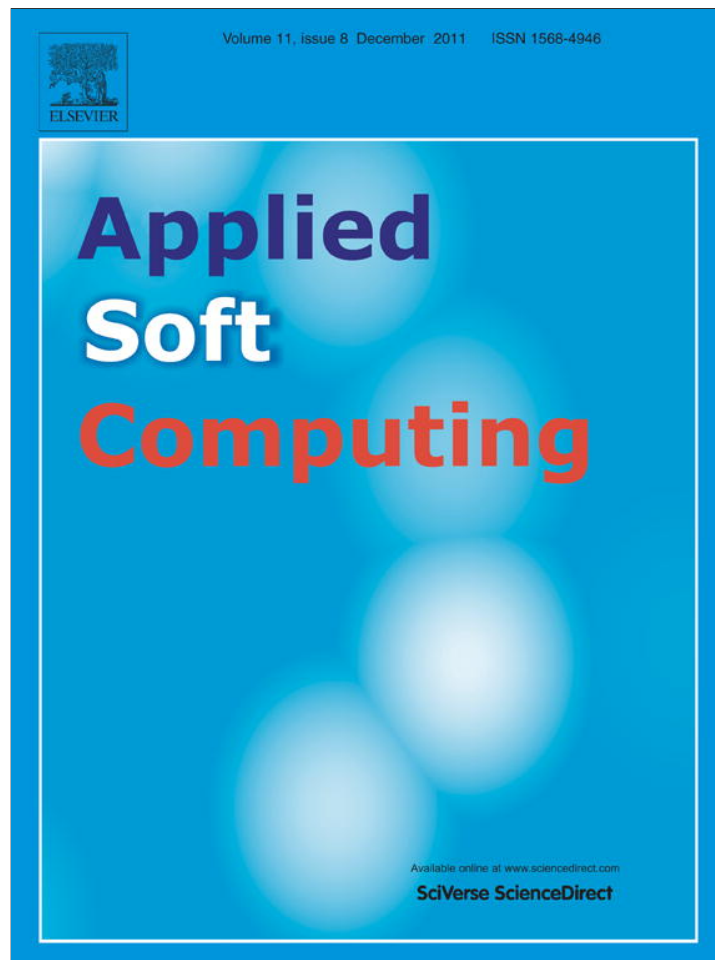


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Review article

Human scalp EEG processing: Various soft computing approaches

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ABSTRACT

Presently high density EEG systems are available at affordable cost, with which the data dimension has gone up considerably. For efficient computation of this high-dimensional data, various soft computing paradigms are receiving increasing attention. In this survey we have identified certain soft computing techniques (by soft computing techniques we mean computational techniques that take into account the inherent uncertainties in the data and/or in the computing model) for pattern recognition/data mining, such as, neural networks, fuzzy logic, evolutionary computation, statistical discrimination and Bayesian inference, which have turned out to be particularly useful in processing human scalp EEG. Wherever possible results of comparative studies among various techniques have been presented. Analyses of EEG for various feature extraction are exceedingly challenging pattern recognition tasks. This survey has shown that on an average the artificial neural networks and Bayesian approaches have emerged more successful in EEG analysis than the other soft computing paradigms. For readability the paper has been kept as little technical as possible. Large number of references have been listed to aid searching for the technical details.

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1. Introduction

In EEG analysis, most methods of analysis follow, explicitly or not, a pattern recognition approach [1,2]. These analyses have important applications in brain computer interface (BCI) [3–5], epilepsy research [6,7], sleep studies [8–10], psychotropic drug research and monitoring patients in critical condition in the ICUs [11,12]. However, automated analysis of EEG data is a huge challenge because of the volume of the data sets and dynamic nature of the signals with high temporal resolutions (in millisecond range). In case of the human scalp EEG signals this challenge has been further augmented by the introduction of high density EEG nets consisting of more than 300 channels [13] and with increasing sample frequency (1000 Hz or more) of digitization by means of advanced technologies.

Human scalp EEG was born in 1920s when the German physician Hans Berger first measured traces of brain electrical activities on the scalp [14,15]. Since then the interpretation of patterns in the scalp EEG, in the most part, has remained a challenging issue. Synaptic activity in the pyramidal neurons (85% of excitatory human cortical neurons are of this type) is the principal source of scalp EEG [16] (p. 914). Modulatory dynamical actions of the neural ensembles, both at local and global scales, give rise to patterns in the scalp EEG [17,18]. With clever quantitative methods it is possible to measure (cognitive) task related integration [19–21] and differentiation [22] (in some sense) from even the single trial EEG signals.

The online epoch identification in human scalp EEG signals has a long history [23]. In this classic, the vision propounded for spatio-temporal data reduction and processing by soft computing approaches, like the Bayesian statistics, in order to bring down the computational loads to a manageable limit, are being largely followed even today [24]. For the sake of computational efficacy it is desirable to keep the analysis linear as far as possible. But, then comes the vital issue – are we not overlooking the nonlinear features? It has been argued in [25] that the advantage of a nonlinear analysis, at greater cost, of the multi-channel noisy scalp EEG data is rather marginal over the corresponding linear methods.

Since the early days of the BCI [26] the need for real time analysis of EEG and ERP has been felt. Linear analysis and soft computing techniques are the two most promising approaches in this regard. In contrast to classical approach of exact computation at a greater cost, which may be prohibitive for the complex problems like multidimensional EEG analysis, soft computing strives to achieve tangible results at reasonable cost by allowing inexactness and uncertainty to be part of the computational model. It includes neural networks, fuzzy logic, statistical discrimination, Bayesian inference and genetic algorithms. This list is of course not exhaustive, but would be sufficient for our purpose in this paper. Here we will be reviewing various soft computing techniques that have been followed for human scalp EEG/ERP processing. Such a review, even if non-exhaustive, would hopefully be useful for the research community.

Broadly speaking, EEG processing has two parts namely, (1) decomposing the complicated signal into simpler components (by FFT, wavelet transform, ICA, PCA, etc.) and (2) bunching those components together in search of specific structures in the data (the pattern recognition part). It is in the latter part, where almost all of these approaches are to deal with uncertainty and therefore they are soft computing approaches.

In the next two sections we will be briefly presenting a physiological overview of scalp EEG and dimensionality reduction of the data respectively. In Section 4 we will be reviewing neural network applications on human scalp EEG, in Section 5 fuzzy systems applications, in Section 6 applications of evolutionary computation, and in Sections 7–9 applications of statistical discrimination, support vector machine (SVM) and Bayesian inference, respectively. Not all

these branches have found equal applications on human EEG. In this survey we have tried to be as exhaustive as we could, sacrificing the technical details, which can be found out in the references. This, we hope, will enhance the readability and usefulness of the paper.

2. Cortical source of scalp EEG

Excitatory postsynaptic potential (EPSP) at the apical dendritic trees of pyramidal neurons is the principal source of the scalp EEG [15,16]. When these neurons receive inputs through their apical dendrites EPSPs are generated in the apical dendritic tree. The apical dendritic membrane becomes transiently depolarized and consequently extracellularly electronegative with respect to the cell soma and the basal dendrites. This potential difference causes a current to flow through the volume conductor from the nonexcited membrane of the soma and basal dendrites to the apical dendritic tree sustaining the EPSPs [1,15].

Some of the current takes the shortest route between the source and the sink by traveling within the dendritic trunk (primary current in blue in Fig. 1). Conservation of electric charges imposes that the current loop be closed with extracellular currents flowing even through the most distant part of the volume conductor (secondary current in red in Fig. 1). Intracellular currents are commonly called primary currents, while extracellular currents are known as secondary, return, or volume currents. With the spatial arrangement and the simultaneous activation of a large population of the cells, as shown in center of Fig. 1, contribute to the spatio-temporal superposition of the elemental activity of every cell, resulting in a current flow that generates detectable scalp EEG signals [15].

Both primary and secondary current contribute to scalp EEG. Macrocolumns of tens of thousands of synchronously activated large pyramidal cortical neurons are thus believed to be the principal sources of scalp EEG because of the coherent distribution of their large dendritic trunks locally oriented in parallel, and pointing perpendicularly to the cortical surface [27]. The currents associated with the EPSPs generated among their dendrites are believed to be at the source of most of the signals detected in MEG and EEG because they typically last longer than the rapidly firing action potentials traveling along the axons of excited neurons [15,28].

3. Dimensionality reduction

Dimension of scalp EEG data at the preprocessing stage is calculated as number of channels \times number of trials (e.g., the way the data representation is made [29]). For dense array EEG consisting of more than 100 channels, a recording session spanning through hundreds of trials each spanning through several seconds or minutes or even hours (in case of say, epilepsy monitoring) with a sample frequency of 1000 Hz or more, the amount of generated data may be of the order of tens or even hundreds of gigabytes. Without some kind of data reduction it would be impossible even to load the data set into the main memory of most modern day work stations. Dimensionality reduction can be done by selecting appropriate channels [30,31] or time epochs or trials [32].

Dimension of EEG at the postprocessing stage is calculated usually in terms of the dimension of the feature space. Dimension reduction (also known as *feature extraction*) is achieved either by projection to a lower dimensional space or by selecting a subspace of the original one [30,33]. In [22] dimensionality reduction has been achieved by projecting EEG from all the channels into a single one dimensional time domain signal. More of it will be discussed in Section 7.

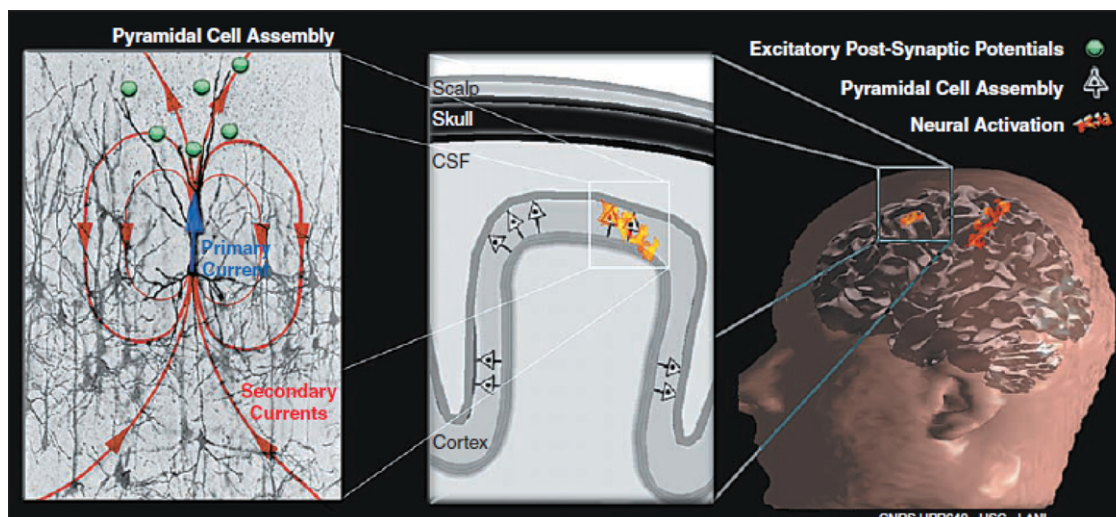


Fig. 1. Left: EPSPs are generated at the apical dendritic tree of a cortical pyramidal cell. Center: Large cortical pyramidal nerve cells are organized in macro-assemblies with their dendrites normally oriented to the local cortical surface. Right: Functional networks made of these cortical cell assemblies and distributed at possibly multiple brain locations are the main generators of EEG signals.

Adopted from [15].

4. Neural networks

This section will be organized in accordance with [34]. Low signal to noise ratio (SNR) in case of scalp EEG is a good reason for using ANN to process them [35].

4.1. Artifact removal

Eye blinks; movements of eyeballs and tongue; face, head and neck muscle contractions; cardiac rhythms; frequency of the alternating current supply to the equipment (steady state 50 or 60 Hz) are the major sources of artifacts in scalp EEG (for a nice overview see Ref. [36]). Some of these may be avoided if the subject follows appropriate guidelines. For the others, automated artifact detection and removal techniques are the most practical solutions. When the patterns of artifacts are different from the patterns of evoked potentials ANNs can theoretically be used to separate the artifacts out from the EEG. Some advancement in this direction has been reported in [37–46].

Various features of artifacts are extracted and fed into the input of an ANN to train it. At the end of the training, success rate of a radial basis function (RBF) network has been reported to be 75% in artifact detection [43].

4.2. Source localization

Interpretation of the clinical EEG almost always involves speculation as to the possible locations of the sources inside the brain that are responsible for the observed activity on the scalp [47]. For excellent reviews see [15,48,49]. However computational cost of most source localization algorithms is prohibitive. An error back propagation NN approach was first proposed to overcome this hurdle in case of dipole source localization [50]. In general dipole source localization problem is an optimization problem – to find optimum coordinate and orientation of dipoles, and hence suitable for being solved by ANN. It is possible to do away with computation intensive head models if there is sufficient input–output data to train the network.

A general ANN system for EEG source localization is illustrated in Fig. 2. According to [51], the number of neurons in the input layer is equal to the number of electrodes and the features at the input can be directly the values of the measured voltage. The network also consists of one or two hidden layers of N neurons each and an output

layer made up of six neurons, 3 for the coordinates and 3 for dipole components. In addition each hidden layer neuron is connected to the output layer with weights equal to one in order to permit a non-zero threshold of the activation function. Weights of inter connections are determined after the training phase where the neural network is trained with predetermined examples from forward modeling simulations [49]. Localization accuracy has been claimed to be less than 5% by various ANN approaches [34,35,50–57] and high accuracy in case of [58]. Clearly ANN approach is not very practical for distributed source models, where sources may consist of any subset of thousands of cortical mesh points [32].

4.3. Sleep studies

K-complexes are said to be the largest events in healthy human sleep EEG [59]. It is natural that ANN had been tried on them quite early with 90% success rate of identification and 8% false positive [60], also [61]. Sleep spindle identification by ANN also started getting attention at the same time [60,62]. A simple feed forward ANN was applied on sleep EEG even earlier [63]. 61–80% accuracy was achieved in classifying seven different sleep stages in infant EEG (wake, movement, sleep stage 1, sleep stage 2, sleep stage 3/4, paradoxical sleep and artifacts) [64]. A pioneering study was undertaken to distinguish sleep EEG power spectrum patterns under the influence of different sleeping pills using ANN [65]. For a detailed review of early ANN applications on sleep studies see [66] (also see [34] for more references).

Use of ANN for automatic sleep stage scoring has been reported in [67] with an average 87.5% agreement with two human experts. A dominating trend in sleep EEG analysis has been – first to extract features (such as shape, frequency and power spectrum) by a suitable wavelet transform (in some cases Fourier transform [68]) and then using these features as input to an ANN [67,69,70]. Accuracy of recognition runs from as low as 44.44% [69] to around 95% in [70]. Automatic recognition of alertness and drowsiness has been performed by three different ANNs with the best performance reported for the learning vector quantization (LVQ) network [71], which is $94.37 \pm 1.95\%$ in agreement with the human experts.

4.4. Epilepsy

EEG analysis is an integral part of diagnosis and monitoring of epilepsy and it has a long history [72]. The effort for automatic

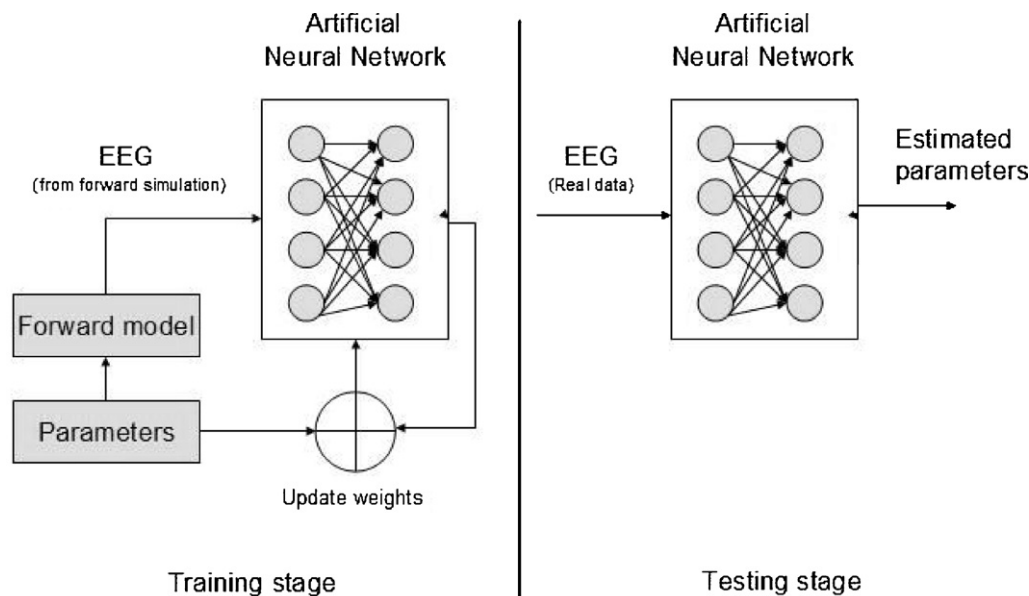


Fig. 2. Block diagram for source localization by artificial neural networks (ANN).

Adopted from [49].

detection of epileptic activities in prolonged EEG recordings is also quite old [73]. Neural networks started being used for epileptic seizure detection since early nineties [74,75] followed by others [76–86]. In case of neonatal seizure detection by error back propagation NN the average detection rate is from 79.6% to 91% [85,86]. Feed forward NN and quantum NN have been used to detect neonatal epileptic seizure with moderate specificity (little over 79% by both types of NN) [87]. Elman networks (ENs) have also been used for seizure detection [88]. These are a form of recurrent NN which have connections from their hidden layer back to a special copy layer. This means that the function learnt by the network can be based on the current inputs plus a record of the previous state(s) and outputs of the network. The results that EN yields are said to be the best with a single feature fed as the input. The overall reported detection accuracy is about 99.6% [88]. Recurrent NN based seizure prediction has been reported in [89]. For better performance of spike detection by NNs, preprocessing of the EEG has been emphasized in [90]. Recurrent NN has been used for seizure EEG classification in [91]. Scalp EEG of 418 epilepsy patients was classified with a multilayer perceptron (MLP), which matched with two human experts in 89.2% instances [92].

Let us conclude this subsection with a prophetic observation of Alan S. Gevins, “Brain electromagnetic signals can be quite useful for providing corroborating evidence about the presence of a seizure disorder and also for determining the site of seizure origin. Therefore, despite their limited clinical impact to date, efforts at automated “epileptiform” transient detection will undoubtedly continue” [93].

4.5. Brain computer interface

BCI started with the seminal paper of Farwell and Donchin [94]. Soon afterward NN was applied to classify the scalp EEG signals during right and left hand movements in the hope of predicting the side of movements before they occurred [95,96]. Power spectrum of extended α -band (5–16 Hz) had been used to train and test an hybrid of K-means and back propagation NN to achieve a classification accuracy of 85–90% [97]. Cascade NN has been used for the same prediction purpose has shown widely varying results depending on the power spectrum of α EEG [98]. 91% or more classification

accuracies were achieved for mere left or right index finger movements discrimination by employing on ANN for each channel and selecting only the ‘best’ classification results [99,100] ([100] also includes right foot movements in addition to the two mentioned earlier).

The performances of a back propagation ANN with four layers have been compared in [101] with two human investigators when both the ANN and the humans were engaged in classifying scalp EEG of six subjects during right middle finger extension tasks. For a cube rotation task in BCI an adaptive NN based algorithm has achieved a 68.3% classification accuracy in [102]. Imagined hand movement in four out of seven subjects is reported to be predictable with 80% accuracy in [103]. In a more recent study fast Fourier transform (FFT) based amplitudes of the EEG have been used as input to a multilayer NN with reported improved accuracy on test sets 80% or more [104]. FFT and NN based EEG classification of intention of right and left elbow movement has been reported in [105,106]. EEG classification of limb movement imagination by NN based on particle swarm optimization has been reported in [107].

4.6. Other patterns

Several studies have been reported pertaining to the analysis of evoked potential (EP) in the scalp EEG using NN [108–110]. Some of them are concerned about visual EPs [109–122], some about auditory EPs [100,110,118,123–134] and some about somatosensory EPs [110,135–139]. For a fundamental treatment of use of NN in the analysis of event related potential (ERP) see Ref. [140].

Using EEG recordings several investigators have developed neural network based systems to assess the vigilance level of the subject under investigation [141–147]. In [147] a Levenberg–Marquardt (LM) multilayer perceptron (MLP) was used to classify EEG signals from 30 subjects for alertness (success rate 93.6%), drowsiness (96.6%) and sleep (90%) (the LM network has been reported to be performing poorer than the LVQ in [71]). The input to the MLP was obtained by spectral analysis of the EEG through a discrete wavelet transform (DWT).

Analysis of maturation level of neonatal brains (28–112 weeks after birth) has been determined using NN on the EEG [148]. NN was used on EEG of 131 children aged between 4 and 16 years to

detect possible abnormality in brain [149]. NN was applied on auditory EP of brainstem to detect hearing impairments in newborns [150]. Attention deficit hyper active (ADHA) disorder is a recognized problem in child psychiatry, in which NNs have been used on EEG to identify symptoms with good success [151,152].

In certain neurological disorders EEG tends to be different from the normal. Tacitly using this fact NN based classification of disordered EEG with respect to the control has been achieved. This was done for headache and migraine [153–155], neuroophthalmological disorder [156], head injury [140], multiple sclerosis [39,157], schizophrenia [158–163], Alzheimer disease [164–167], Parkinson's disease [167], Huntington's disease [162,168–171], depression [161] and alcoholics [172,173]. Probabilistic NN has also been used for EEG classification in [174] with moderate success and slightly poorer performance than SVM, but with much better performance in [175]. For some clinical applications of NN on EEG see Section 4 of [176].

MLP and EN have been used on EEG to determine the depth of anesthesia during surgery with 99% success for the EN [177] (for a survey of applications of NN on EEG during anesthesia see Ref. [178]). EN has been shown to perform better on human visual evoked potential (VEP) than the k nearest neighbor (kNN) algorithm [179]. Continuous monitoring of brain state by means of NN application on EEG of the critically ill patients in the intensive care unit (ICU) has been reported in [12,180]. Use of NN on EEG under the effects of drugs (sedatives) in order to classify the effects due to different drugs has been reported in [181,182]. Classification of online scalp EEG by NN during three different mental tasks has been performed with 70% accuracy, but with only 5% mis-classification [183]. Convolutional NN has been used in BCI for classifying EEG during different activities with 95% accuracy [184].

5. Fuzzy logic

Fuzzy logic based analysis of human scalp EEG started with the pioneering paper [8]. Fuzzy clustering and neuro-fuzzy techniques have remained the most notable methodologies in this regard.

5.1. Fuzzy clustering

Cluster analysis is based on partitioning a collection of data points into a number of subgroups, where the objects inside a cluster (a subgroup) show a certain degree of closeness or similarity. Hard clustering assigns each data point (feature vector) to one and only one of the clusters, with a degree of membership equal to one, assuming well defined boundaries between the clusters. This model often does not reflect the description of real data, where boundaries between subgroups might be fuzzy, and where a more nuanced description of the object's affinity to the specific cluster is required [10]. In case of human EEG this was first utilized in [8] (before this fuzzy clustering was applied on sleep EEG of chimpanzee [185]). An efficient human sleep EEG data classification has been reported in [10] by means of unsupervised fuzzy partition-optimal number of classes (UFP-ONC), which is a combination of fuzzy k -means (FKM) algorithm [186] and fuzzy maximum likelihood estimation. This has been able to decompose the sleep EEG from a single subject into optimum number of distinct classes, which has been treated as a priori unknown [10,187,188].

A different fuzzy clustering algorithm was used in [189] for EP identification in low signal to noise ratio (SNR) EEG. In this FKM algorithm has been applied with the number of clusters determined by the criterion proposed in [190]. Trials with prominent (same) EP were grouped together using fuzzy clustering before being averaged for extraction of the EP. Single instances of EP have been reported to be classified up to 95% accuracy. FKM clustering (also known as fuzzy c -means clustering) was used in conjunction with

an ANN to classify epileptic spikes (ES) in scalp EEG [191]. However the performance is not very impressive.

Fuzzy if-then rule-based online classification of a single subject's EEG signal during pain and no pain experiences has been reported in [192] with only 64% overall classification accuracy, which is slightly poorer than the corresponding hidden Markov model (HMM) classification studied on the same data set. A fuzzy classification technique for epilepsy risk level has been proposed in [193].

5.2. Neuro-fuzzy techniques

Combination of NN and fuzzy logic gives a powerful soft computing methodology, which has been applied on human EEG with mixed success. In one of the first applications auditory evoked potential (AEP) from the EEG of a patient under anesthesia was analyzed by an NN. The output of the NN was utilized as input to a fuzzy if-then rule-based controller, which controlled the dosage of the anesthetic drug. The performance was graphically compared with a trained anesthetist during a real surgery [194].

About 88.2% infant sleep-wake stage classification on the test EEG data has been achieved by ANFIS-based classifier [195] (Fig. 3). The architecture is in Fig. 3. Layer 1 is the fuzzification layer. X_1 , X_2 , and X_3 are three of the input variables, each with two associated fuzzy concepts (A_i and B_i). Layer 2 generates all the possible rules of the form IF X_1 is A_1 and X_2 is B_2 and X_3 is A_3 , with a T-norm operator (\cdot), considering one fuzzy concept per input variable. The output of layer 2 is a strength parameter for each of the rules. Each node at layer 3 performs a linear combination of the rules and uses a sigmoidal function to determine the degree of belonging of the input pattern to each class (C_1 , C_2 , C_3). In another study ANFIS classifiers were used on features extracted from EEG by wavelet transformations (WTs) for classification pertaining to five different classes with a total accuracy of 98.68% [196]. WT on EEG followed by ANFIS could classify normal subjects from epileptic patients with 93.7% and 94.3% respectively, which is slightly higher than that achieved by an MLP [84]. WT followed by ANFIS has been used to analyze EEG pertaining to left and right hand movements [197], state of alertness [198]. Neuro-fuzzy NN has been used to determine the states of fatigue or alertness in drivers [199]. EEG feature extraction by Lyapunov exponent followed by ANFIS classification was used to detect changes in the signal [200]. A comparative study of neuro-fuzzy classifiers with some other classification methods is also available [201]. For a comprehensive treatment of the subject see Ref. [202].

Combining adapted resonance theory (ART) NN with fuzzy logic, fuzzy ARTMAP NN was created [203], which has found several applications in human EEG processing [169,204–208], often with classification success rate of 90% or above. Very recently a faster self-organizing fuzzy neural network has been applied in BCI with up to 70% processing time reduction [209].

5.3. Other fuzzy systems

After extracting features from EEG by DWT fuzzy SVM (FSVM) has been applied for the classification [210]. However FSVM is reported to have given poor results on classification of schizophrenic EEG from the control subjects [211]. Features extracted from EEG using wavelet packet have been sorted by fuzzy logic for optimum performance [212]. Fuzzy if-then rules have been used on features extracted by time frequency analysis of EEG in order to determine the depth of anesthesia on 22 patients [213]. Fuzzy rule based detection of α -band activity has been proposed in [214]. EEG based use of a fuzzy controller has been proposed to administer anesthesia in [215].

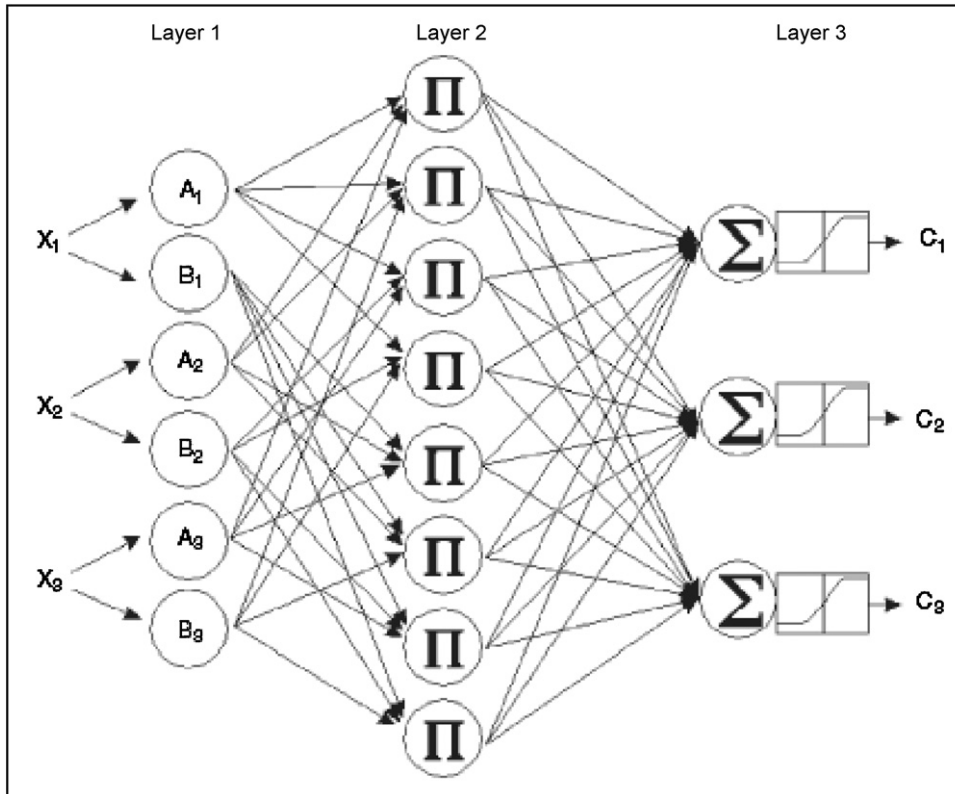


Fig. 3. A simple adaptive neuro-fuzzy inference system (ANFIS) for infant sleep-wake stage classification.

Adopted from [195].

6. Evolutionary computation

Signals in medicine, such as EEG, processing is subject to several important constraints. First, the number of signals to be processed is high, and often tightly interdependent. Second, signals are unique, in the sense that the circumstances under which they were obtained are normally not repeatable. Third, given the characteristics of their sources, medical signals are often very noisy. Finally, in some cases information about the signals is required in real time in order to take crucial decisions [216]. Genetic algorithm (GA) was applied on EEG during different mental tasks in order to classify them in task specific categories. The goal was achieved with 76% accuracy [25]. Genetic programming (GP) has been applied on human scalp EEG for epileptic pattern recognition [217] with success rate of 93% or more (in intracranial EEG seizure precursor features have been detected by GP in [218]). GP has been used for normal EEG classification in [219]. Epilepsy risk assessment with GA has been done in [220,221].

7. Statistical discrimination

Statistical discriminants are standard tools for classification of multidimensional patterns (for a general introduction see Ref. [222]). Their need in human scalp EEG classification has long been felt [23]. Using them on scalp EEG, classification of dyslexia patients was performed in [223]. EEG of mild head injury patients was classified (with respect to a group of normal control subjects) by statistical discriminants with more than 90% accuracy in [224,225]. [226] presents a review of classification of scalp EEG by discriminators in case of traumatic brain injury. Discriminants have been used to classify EEG belonging to subjects with neuropsychiatric disorders [227]. Unfortunately, very little detail is available of the discriminators implemented in [224–227].

Scalp EEG of normal human subjects has been classified during rapid serial visual presentation (RSVP) of ‘interesting’ and ‘uninteresting’ scenes by statistical discriminants [22,228,229]. Discriminant analysis has been performed in single trials on the weighted sum of all the scalp channels, where the optimum weight has been selected by fine tuning a logistic regression (LR) function (for a nice exposition of LR see Ref. [230]) with the help of gradient descent method [22]. Then normalized projection of signal from each channel on this average is calculated. Intensity of this projection is used to classify signals between interesting (91.8% classification accuracy) and uninteresting scenes (98.3% classification accuracy) [228].

Although LR is more robust, it is a less efficient classifier and takes more resources to compute compared to the normal statistical discriminators [231]. A study was undertaken to compare performance between Fisher’s discriminant (FD, see [232,233] for description) and LR on the scalp EEG of three subjects (two males and one female, mean age thirty years, all of them left handed). They did not have any known neurological or vision disorder. The data was collected using 256 channel Hydrocell Geodesic Sensor Net (Electrical Geodesics, Inc., Eugene, OR) during a series of RSVP tasks at a rate of 3 grey level satellite images per second [234]. The analysis was performed on single trials. LR turned out to be good in identifying target, but poor in identifying non-target data (Table 1).

Table 1
Average performance of LR vis-à-vis FD on the EEG of three subjects during RSVP (3 images per second) of three different targets vs. non-target. ROC area means the area under the receiver operator characteristic (ROC) curve.

	LR	FD
Target	0.9752	0.7601
Non-target	0.5768	0.8770
ROC area	0.9311	0.8700

Table 2

Average performance of LR vis-à-vis FD on the EEG of three subjects during RSVP (3 images per second) of target tank and target truck in different sessions (each consisting of about 300 trials) in each of which only one type of target images are mixed with non-target images roughly at 1:4 ratio.

	LR	FD
Tank	0.6186	0.9858
Truck	0.7623	0.9751
ROC area	0.7067	0.9939

On the other hand FD was poor in identifying target data, but much better in identifying non-target data (Table 1). FD was also good in separating various pairs of target EEG data (see Table 2 for an example). The general conclusion was that there is no particular discriminator uniformly suitable for all types of EEG data. Different discriminators perform differently on different data sets [234]. FD was used on EEG after feature extraction by a combination of continuous WT and student *t*-statistic with the best classification accuracy in the 2003 BCI competition [235]. FD was used for random classification of EEG channels for BCI in [236] with a very moderate accuracy of 56.66%. A comparison of FD and two of its variants with SVM and *k* nearest neighbor (kNN) algorithm on EEG data before onset of finger movements appears in [237]. The outcomes are presented in Table 3. For a review of applications of linear discriminant analysis in BCI research see Ref. [238].

LR has been compared with NN on seizure EEG data [83]. Classification accuracy of two different MLPs has been reported to be more than 91% compared to 89% for the LR. Superior performance of NN over LR has been reported in [239,240]. On an average LR had performed better on the single trial EEG than a conventional spatial pattern (CSP) based classifier [241].

A statistical discriminant was used to classify EEG signals belonging to schizophrenic patients for negative and positive features associated with the symptoms. 78% classification accuracy for schizophrenia was achieved on a test data set (disjoint from the training data) with 85% specificity [242]. Quadratic discriminant function was applied on EEG of 33 subjects to classify among different tasks with 93% accuracy for the training data and 85% accuracy for the testing data [243].

8. Support vector machine

Despite greater difficulty in implementation and longer running time on test data compared to the NN and linear discriminants, SVM has become a popular classification algorithm for the EEG for its usually higher classification accuracy compared to the former. For an excellent tutorial on SVM see Ref. [244]. The primary motivation behind SVM is to directly deal with the objective of generalization from training data to testing data with minimization of error and complexity of the learning algorithm [25]. Table 3 shows superior performance of SVM on EEG data. A recent study on classification (vis-à-vis a human expert) of neonatal EEG of six infants has shown that SVM has outperformed the FD and NN (Fig. 4) [245].

Table 3

Test set error (\pm std) for classification at 120 ms before keystroke. 'mc' refers to the 21 channels over (sensori) motor cortex, 'all' refers to all 27 channels. RFD and SFD stand for regularized and sparse FD respectively. ch stands for channel.

Filter	ch's	FD	RPD	SFD	SVM	k-NN
<5 Hz	mc	3.7 \pm 2.6	3.3 \pm 2.2	3.3 \pm 2.3	3.2 \pm 2.5	21.6 \pm 4.9
<5 Hz	all	3.3 \pm 2.5	3.1 \pm 2.5	3.4 \pm 2.7	3.6 \pm 2.5	23.1 \pm 5.8
None	mc	18.1 \pm 4.8	7.0 \pm 4.1	6.4 \pm 3.4	8.5 \pm 4.3	29.6 \pm 5.9
None	all	29.3 \pm 6.1	7.5 \pm 3.8	7.0 \pm 3.9	9.8 \pm 4.4	32.2 \pm 6.8

Reproduced from [237].

Artifacts such as, eye blink potential and electrocardiogram (ECG) have been removed from EEG using SVM [246]. A nonlinear SVM was applied to distinguish P300 EEG epochs from the other EEG signals during visualization of different words with 84.5% accuracy [247]. In another application on P300 based speller classification a self-supervised SVM has been applied to reduce the training efforts [248]. In [249] average P300 classification accuracy by SVM has been reported to be above 95%. Superior performance of SVM than linear discriminant analysis and *k* nearest neighbor classifier on the EEG of five subjects during limb and tongue movements has been reported in [250]. Better performance of SVM over PNN and multilayer PNN in EEG classification has been reported in [174]. 90% accuracy in EEG classification by SVM during left, right finger movements has been reported in [251]. SVM as part of ensemble classification for EEG has been considered in [252].

9. Bayesian approaches

9.1. Source localization

If J_n is an *n*-dimensional vector of cortical sources and M_p be a *p*-dimensional measurement of scalp EEG, where *n* and *p* are number of sources and number of channels respectively. Then by Bayes theorem

$$p(J_n|M_p) = \frac{p(M_p|J_n)p(J_n)}{p(M_p)}, \tag{1}$$

where $p(A|B)$ is the conditional probability of event *A*, given event *B*. $p(M_p)$ is constant. The configuration J_n for which maximum of (1) will be achieved is the most probable source of M_p . This is called *maximum a posteriori* (MAP) estimation [253,254]. We can write $p(J_n|M_p) = (1/Z)\exp(-U(J_n))$, *Z* is a normalization constant and *U* is an 'energy' function. Taking logarithm and treating $p(M_p)$ as a constant throughout, we can write $U(J_n) = U_1(J_n) + \lambda U_2(J_n)$, where λ is a constant, and $U_1(J_n)$ and $U_2(J_n)$ are associated with $p(M_p|J_n)$ and $p(J_n)$ respectively. $U_1(J_n) = \|M_p - GJ_n\|$, where *G* is a *p* \times *n* mixing matrix made out of the head model of the subject. $U_2(J_n) = U_s(J_n) + U_t(J_n)$, where U_s and U_t are associated with spatial and temporal priors respectively. Five different algorithms were used in [253] to calculate the MAP in (1). In [254] Bayesian MAP has been used to estimate error in the reconstructed sources. Unlike [253], in [254] the prior has been modeled by chi-square distribution function.

Bayesian model averaging has been applied for EEG source localization, which determined the posterior probability of the sources according to the best available model [255]. Repeated Bayesian estimation of maximum entropy of EEG has been used for the source localization [256]. A hybrid of two source models – equivalent current dipole (ECD) model and distributed source (DS) model has been proposed in [257]. Source reconstruction has been performed under suitable spatial and temporal constraints estimated by Bayesian method. EEG source reconstruction was done in [258] according to both ECD and DS models by formulating the inverse problem as Bayesian inference, like in (1). The forward model was constructed by Markov chain Monte Carlo (MCMC) method.

A general framework for Bayesian interpretation of brain images has been proposed in [259]. It has been applied for EEG source localization in [24]. Source localization has been performed with no prior, accurate prior, inaccurate prior, and a mixture of accurate and inaccurate prior. Results obtained on spherical head model with simulated data under different SNR and three different inverse methods subject to Bayesian expectation maximization. A result is shown in Fig. 5. Automatic selection of multiple cortical sources with compact support in a DS model has been achieved in [260] with a new application of [259]. In another application evoked and induced responses with respect to a stimulus has been

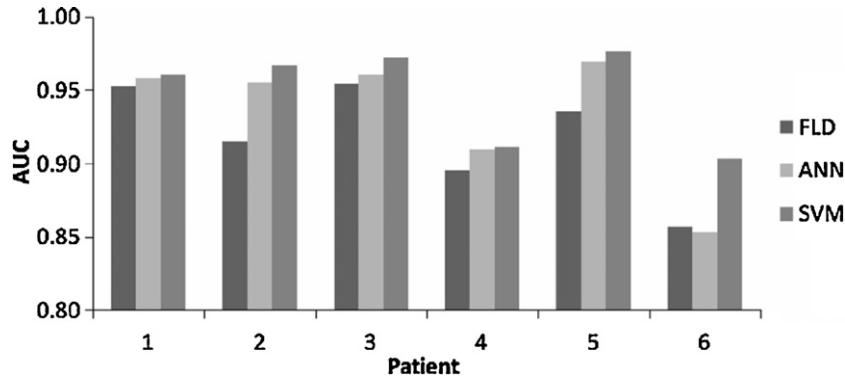


Fig. 4. Six infants shown in abscissa. Performance measure is given by area under curve (AUC) of the ROC curve. FLD stands for Fisher's linear discriminant. Adopted from [245].

reconstructed in the cortical surface from scalp EEG data [261]. Bayesian learning has been utilized to identify common sources of EEG and fMRI (functional Magnetic Resonance Imaging) in human subjects in [262].

9.2. Brain computer interface

Bayesian NN was used on EEG to detect imagined finger movements in [263] with a typical accuracy of 75%. A real time BCI was designed with minimum training and using only one channel EEG data with $86.5 \pm 6.9\%$ classification accuracy for cursor movement task in [264]. The minimum training was possible under a

Bayesian paradigm. A Bayesian inference scheme to predict continuous cursor movement has been proposed in [265,266]. A dynamic Bayesian network (DBN) model has been used to predict the movement intention, where the DBN has learned from the EEG and EMG (electromyogram) [267].

A comparative study among Bayesian graphical network, neural network, Bayesian quadratic, Fisher linear and hidden Markov model as classifiers of EEG for BCI applications has been presented in [268] (Table 4). BGN and Bayesian quadratic classifier seem to have performed better than others. Bayesian linear discriminant analysis has been applied for EEG classification in BCI in [269], with a superior performance than SVM and linear discriminant.

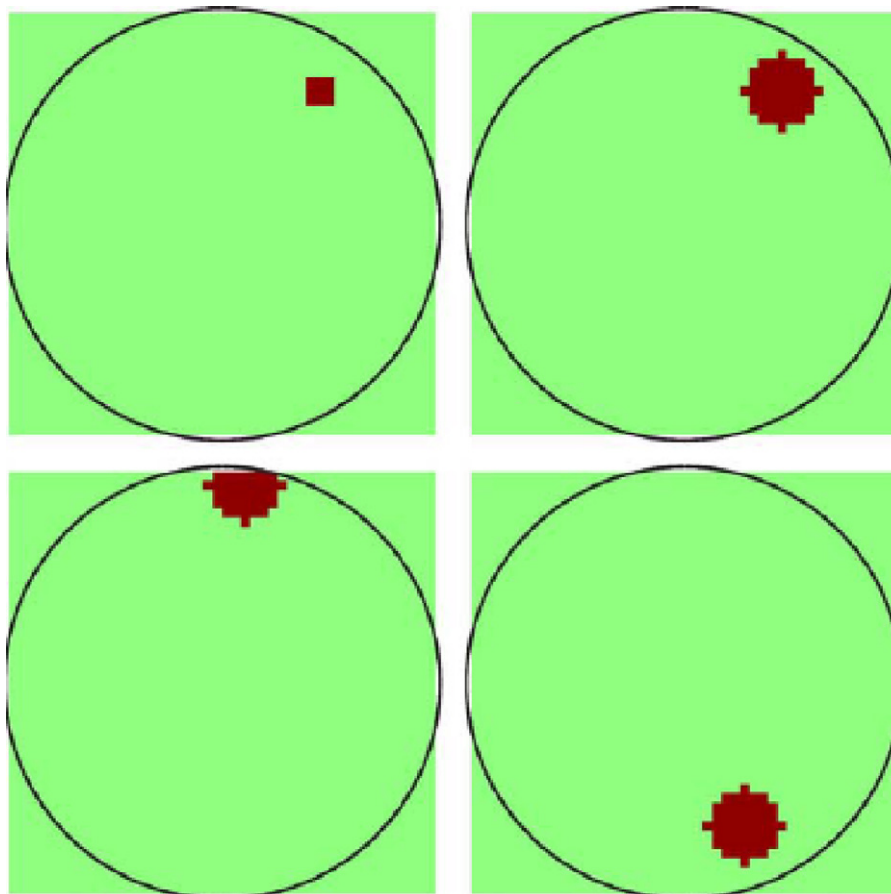


Fig. 5. Example of a source used in the simulations (top left) with the corresponding accurate location priors (top right), as well as inaccurate location priors (close, bottom left, and distant, bottom right). Adopted from [258].

Table 4

The Bayesian graphical network (BGN), neural network, Bayesian quadratic classifier, Fisher linear and hidden Markov model (HMM) are compared for classification of binary combinations of five mental tasks. The results in the table are averaged over ten different possible binary combinations of mental tasks.

Subject	BGN	Neural network	Bayesian	Fisher lilies	HMM
1	94.07 ± 2.2	92.48 ± 2.9	93.78 ± 2.8	91.15 ± 2.7	70.18 ± 8.8
3	87.43 ± 3.9	85.04 ± 4.3	89.22 ± 3.5	82.77 ± 4.1	64.10 ± 9.1
	82.48 ± 2.8	82.61 ± 3.0	86.58 ± 3.4	81.79 ± 3.1	62.43 ± 7.8
6	90.31 ± ±2.7	89.39 ± 3.1	92.49 ± 3.2	90.38 ± 3.1	64.61 ± 8.3
Means	88.57 ± 3.0	87.38 ± 3.4	90.51 ± 3.2	86.63 ± 3.3	65.33 ± 8.5

Reproduced from [268].

9.3. Bayesian classification

There are two standard approaches to EEG classification – *discriminative* and *generative*. Bayesian classification falls under the generative class. For a nice overview see Ref. [270]. In a generative approach, we define a model for generating data V belonging to particular mental task $c \in \{1, \dots, C\}$ in terms of a distribution $p(V|c)$. Here, V will correspond to a time-series of multi-channel EEG recordings, possibly preprocessed. The class c will be one of the mental tasks. For each class c , we train a separate model $p(V|c)$, with associated parameters Θ_c , by maximizing the likelihood of the observed signals for that class. We then use Bayes rule to assign a novel test signal V^* to a certain class c according to: $p(c|V^*) = \frac{p(V^*|c)p(c)}{p(V^*)}$. That model c with the highest posterior probability $p(c|V^*)$ is designated the predicted class [270].

Input output Hidden Markov model (IOHMM, see Ref. [271], and Fig. 7(d) for the architecture) based classification of EEG, which is a special case of Bayesian classification, has been applied in BCI [270]. IOHMM has performed better than HMM, Gaussian mixture model (GMM) and MLP with reduced classification error rate. HMM was applied on whole night EEG of nine subjects for sleep stage classification with accuracy ranging from 26% (rapid eye movement sleep) to 86% (wake stage) [272]. To overcome the problem of nonstationarity in EEG signals HMM has been introduced, which then according to the scheme presented in Fig. 6 determines if the movement intention is on left or right by evaluating the expression $\text{MAX}(P_P(V|HMM_L), P_P(V|HMM_R))$ [273]. The online classification

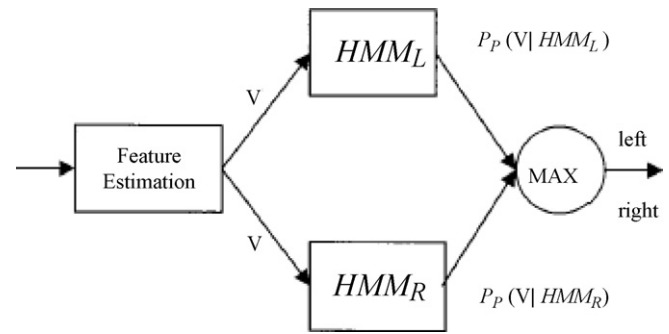


Fig. 6. BCI system comprising HMM_L for left movement feature selection and HMM_R that for the right. Adopted from [273].

rate occurring in four healthy subjects varied between 75% and 95% [274]. For theory and some applications of HMM see Refs. [275,276]. HMM on EEG was used to classify arousal and sleep states in [277]. Various HMM architectures have been shown in Fig. 7. A comparative study of their performances on human EEG data has been presented in [278]. HMM along with *Principal Component Analysis* (PCA) and SVM has been applied on EEG to classify left right movement in [279].

Kernel PCA and HMM are combined to identify mental fatigue features in EEG in [280] with a classification accuracy of 88%. The

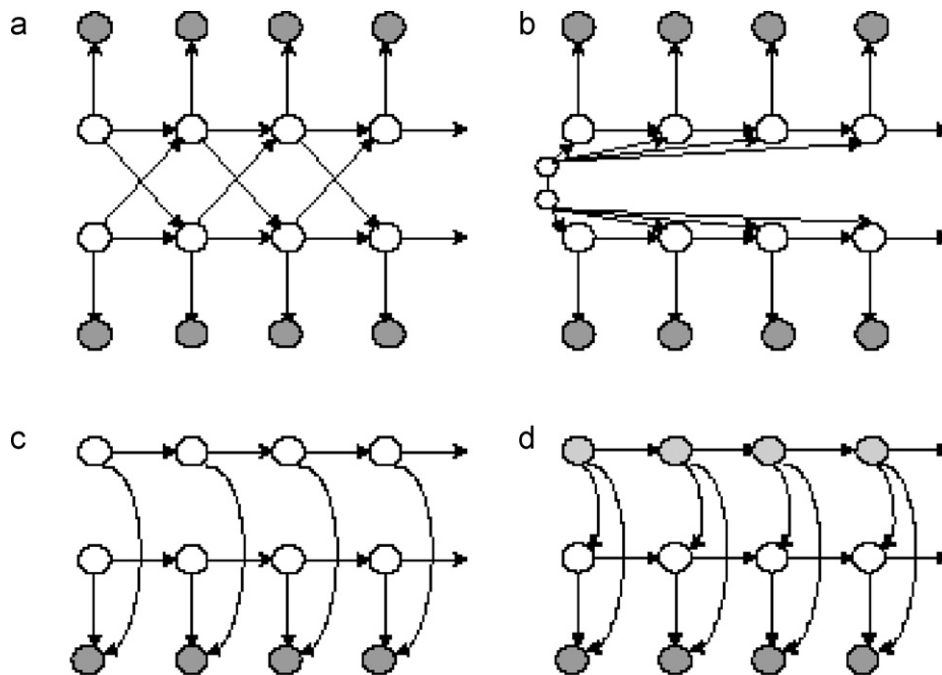


Fig. 7. Various HMM architectures. The empty circles are the hidden states and the shaded ones are observation nodes, the lightly shaded ones (in d) are input nodes. (a) Standard coupled HMMs; (b) event coupled HMMs; (c) factorial HMMs; (d) input–output HMM. Adopted from [278].

signal was collected during prolonged viewing at visual display terminal (VDT). HMM has also found applications in designing and validating seizure prediction algorithms [281].

10. Conclusion

EEG signals are multidimensional, nonstationary (i.e., statistical properties are not invariant in time), time domain biological signals, which are not reproducible. It is supposed to contain information about what is going on in the ensemble of excitatory pyramidal neuron level, at millisecond temporal resolution scale. Since scalp EEG contains considerable amount of noise and artifacts, and exactly where it is coming from is poorly determined, extracting information from it is extremely challenging. So far the two major paradigms used to understand scalp EEG are – segregation (classification, clustering, etc.) and integration (synchronization, coherence, etc.), both of which are computation intensive. The current explosion of interest in BCI, on the other hand, underscores the need of online processing. This is a compelling reason for the popularity of soft computing algorithms in human scalp EEG processing.

The class of soft computing algorithms is not precisely defined. Any algorithm which employs inexact or approximate calculations may fall under this category. But for this paper by a soft computing algorithm we have understood any technique falling under one or more of the following categories: neural networks, fuzzy logic, evolutionary computation, statistical discrimination, support vector machine and Bayesian approaches. From a literature survey it appears that neural networks and Bayesian approaches are the two most popular choices in EEG processing. Linear statistical discriminants are easier to implement, but support vector machines give (many a times marginally) better classification accuracy. It is a choice between cost of implementation and significance of difference in performance. The popularity of fuzzy logic and genetic programming based techniques in human scalp EEG processing are yet to catch up with the remaining four. In general there is no 'good' or 'bad' technique in EEG processing. An 'efficient' technique is to be chosen depending on the data set and processing goal. In this sense, along with more 'exact' computing, the soft computing technique paradigms discussed in this paper constitute major human scalp EEG processing methodologies for the last three decades.

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